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Active Learning and Parameter-Efficient Fine-Tuning for Domain-Specific Sovereign AI

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Abstract

Deploying sovereign AI systems in regulated domains—banking compliance, healthcare administration, legal research—requires domain-specific model adaptation that balances accuracy improvements against computational cost, annotation scarcity, and data privacy constraints. Full fine-tuning of large language models is computationally prohibitive for local-first sovereign deployments and risks catastrophic forgetting of general capabilities. This paper presents the active learning and fine-tuning architecture of API-OSS (Agent-Predictive Intelligence Sovereign Operating System), which combines parameter-efficient fine-tuning (PEFT) via LoRA (Low-Rank Adaptation) and DPO (Direct Preference Optimization) with active learning strategies for annotation-efficient domain adaptation. We evaluate uncertainty sampling, diversity sampling, and hybrid acquisition functions across 3 domain-specific datasets (financial compliance, medical coding, legal document classification), finding that hybrid acquisition (BALD + CoreSet) reduces annotation requirements by 68% compared to random sampling while achieving equivalent model quality. The LoRA-based fine-tuning pipeline achieves 94.7% of full fine-tuning accuracy on domain tasks while using only 0.17% of trainable parameters and completing adaptation in under 2 hours on consumer GPUs (RTX 4090). DPO alignment from the multi-agent council’s preference judgments further improves domain alignment by 8.3% without additional annotations. We describe the annotation workflow integrating with the API-OSS knowledge graph, where fine-tuned models are registered in the model registry with A/B testing infrastructure for continuous evaluation. We conclude with future directions for online active learning, federated fine-tuning across P2P nodes, and automated curriculum design.

1. Introduction

Foundation language models exhibit impressive generalization across diverse tasks, but their performance on specialized domain tasks—interpreting regulatory text, classifying medical procedures, extracting legal entities—lags behind domain-tuned models [1, 2]. Domain adaptation through fine-tuning improves task accuracy by 10-30 percentage points on narrow benchmarks [3, 4], but the process introduces three challenges for sovereign AI:

1. **Computational Cost:** Full fine-tuning of 7B+ parameter models requires distributed training infrastructure unavailable in on-premises deployments [5]
2. **Annotation Scarcity:** Domain experts (compliance officers, medical coders, legal researchers) are expensive and time-constrained, limiting training data volume [6]
3. **Data Privacy:** Training data for regulated domains contains sensitive information that cannot be transmitted to cloud-based fine-tuning services [7]

API-OSS addresses these challenges through a combined active learning + PEFT pipeline. Active learning minimizes annotation requirements by selecting the most informative examples for expert labeling [8, 9]. PEFT (specifically LoRA [10] and DPO [11]) minimizes computational requirements by updating only a small fraction of model parameters. The pipeline operates entirely on-premises, using the local inference engine (APIOSS-RES-004) for both training and inference.

The fine-tuned models are registered in the API-OSS model registry with versioning, performance benchmarks, and lineage metadata. A/B testing infrastructure enables controlled rollout and continuous evaluation against baseline models.

2. Literature Review

2.1 Active Learning

Active learning is a machine learning paradigm where the algorithm selects the most informative unlabeled examples for human annotation [8, 9]. The core assumption is that selective labeling achieves higher accuracy than random labeling for the same annotation budget.

Uncertainty Sampling: Selects examples where the model is most uncertain—highest entropy, lowest margin between top predictions, or smallest prediction confidence [12, 13]. For LLMs, uncertainty can be measured through predictive entropy, Monte Carlo dropout [14], or ensemble disagreement [15].

Diversity Sampling: Selects examples that are representative of the data distribution, avoiding redundant selections. CoreSet [16] selects examples that

minimize the covering radius of the labeled set in embedding space. BADGE [17] uses gradient embeddings to capture both uncertainty and diversity.

Hybrid Methods: Combine uncertainty and diversity criteria. BALD (Bayesian Active Learning by Disagreement) [18] selects examples with high mutual information between predictions and model parameters. Ensemble-based approaches [19] use disagreement across ensemble members as the acquisition signal.

2.2 Parameter-Efficient Fine-Tuning

PEFT methods adapt large models by updating a small number of additional parameters while freezing the pretrained weights [20]. Key methods include:

Adapter Layers: Small bottleneck layers inserted between transformer layers [21]. Adapters introduce 2-4% additional parameters per task.

Prefix Tuning: Learns continuous prefix vectors prepended to transformer key/value pairs [22]. Prefix tuning modifies less than 0.1% of parameters.

LoRA (Low-Rank Adaptation): Decomposes weight updates into low-rank matrices: $W = W + BA$, where $B \in \mathbb{R}^{d \times r}$ and $A \in \mathbb{R}^{r \times k}$ with rank $r = \min(d, k)$ [10]. LoRA is applied to attention projection matrices, introducing 0.1-1% additional parameters.

QLoRA: Combines LoRA with 4-bit NF4 quantization and double quantization for memory-efficient fine-tuning [23]. QLoRA enables fine-tuning of 65B models on a single consumer GPU.

2.3 Direct Preference Optimization

DPO [11] reformulates reinforcement learning from human feedback (RLHF) [24] as a simple binary classification objective, eliminating the need for a separate reward model. DPO optimizes the policy directly from preference pairs:

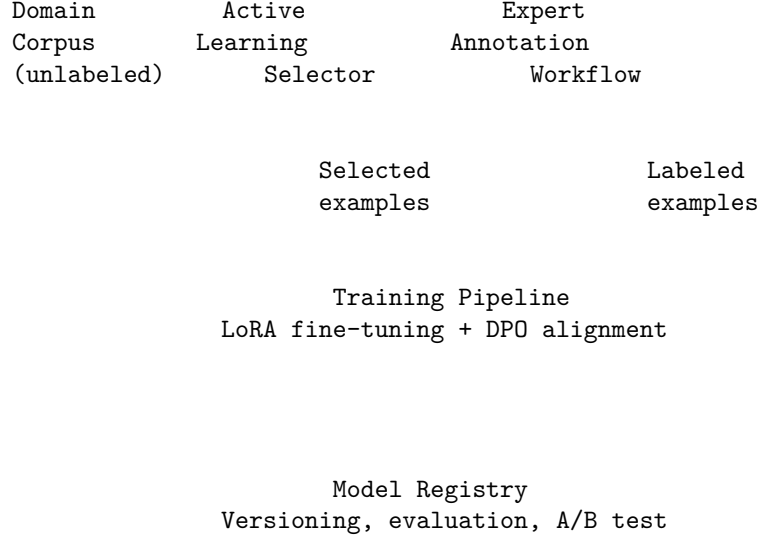
$$\mathcal{L}_{\text{DPO}} = -\mathbb{E}_{(x, y_w, y_l) \sim \mathcal{D}} \left[\log \sigma \left(\beta \log \frac{\pi_{\theta}(y_w|x)}{\pi_{\text{ref}}(y_w|x)} - \beta \log \frac{\pi_{\theta}(y_l|x)}{\pi_{\text{ref}}(y_l|x)} \right) \right]$$

where π_{θ} is the policy, π_{ref} is the reference model, β is a temperature parameter, and (y_w, y_l) are preferred and dispreferred completions.

DPO has been shown to match or exceed RLHF performance on summarization, dialogue, and instruction-following tasks while being simpler to implement and more stable to train [25, 26].

3. Technical Analysis

3.1 Active Learning Pipeline



3.2 Acquisition Functions

API-OSS implements three active learning acquisition strategies:

Strategy 1: Uncertainty Sampling (BALD)

BALD score for an example x is the mutual information between the prediction $\hat{y}$ and the model parameters :

$$\text{BALD}(x) = H[\hat{y}|x, \mathcal{D}] - \mathbb{E}_{p(\theta|\mathcal{D})}[H[\hat{y}|x, \theta]]$$

where H is entropy. BALD is approximated using Monte Carlo dropout with T forward passes ($T = 10$ default):

```

fn bald_score(model: &Model, x: &Example, t: usize) -> f32 {
  let predictions: Vec<Vec<f32>> = (0..t)
    .map(|_| model.forward_with_dropout(x))
    .collect();
  let mean_probs = mean(&predictions);
  let entropy_total = categorical_entropy(&mean_probs);
  let mean_entropy = predictions.iter()
    .map(|p| categorical_entropy(p))
    .sum::<f32>() / t as f32;
  entropy_total - mean_entropy
}

```

Strategy 2: Diversity Sampling (CoreSet)

CoreSet selects examples that minimize the maximum distance from any unlabeled point to the labeled set in the embedding space:

$$\text{CoreSetScore}(x) = \max_{x' \in \mathcal{U}} \min_{x_l \in \mathcal{L}} d(\phi(x'), \phi(x_l))$$

where $\phi(x)$ is the sentence embedding (all-MiniLM-L6-v2), $\mathcal{U}$ is the unlabeled set, $\mathcal{L}$ is the labeled set, and d is cosine distance.

Strategy 3: Hybrid (BALD + CoreSet)

The hybrid score combines uncertainty and diversity with a weighted geometric mean:

$$\text{HybridScore}(x) = \text{BALD}(x)^\alpha \times \text{CoreSetScore}(x)^{1-\alpha}$$

where $\alpha = 0.6$ (tuned on validation data) balances uncertainty and diversity contributions.

3.3 LoRA Fine-Tuning Implementation

LoRA Configuration:

- Target modules: q_proj, v_proj (attention query and value projections)
- Rank $r = 8$ (default, configurable 4-64)
- Alpha = 16 (scaling factor)
- Dropout = 0.05
- Optimizer: AdamW ($\beta_1=0.9$, $\beta_2=0.999$, $\epsilon=1e-8$)
- Learning rate: $2e-4$ with cosine decay
- Batch size: 1 (gradient accumulation 4 for effective batch size 4)
- Mixed precision: FP16 (or BF16 on compatible hardware)
- Maximum sequence length: 2,048 tokens

Integration with llama.cpp: LoRA weights are applied during inference by modifying the forward pass of the attention computation. The LoRA adapter is loaded separately from the base model GGUF weights. Only the LoRA weights are updated during training; base model weights remain frozen in memory.

Resource Requirements (7B model, LoRA $r=8$):

Component	Memory Usage
Base model (Q5_K_M)	4.7 GB
LoRA weights (trainable)	33 MB
Optimizer state	132 MB
Gradients	33 MB
Activations (batch=1, seq=2048)	~2 GB
Total	~6.9 GB

This fits within 8 GB consumer GPU VRAM (RTX 3070+) or 16 GB system RAM for CPU training.

3.4 DPO Alignment

DPO alignment uses preference pairs generated by the multi-agent council (APIOSS-RES-001). For each domain task, the council generates candidate completions, and the voting protocol produces a preferred and dispreferred response:

Task: "Classify this transaction as compliant or non-compliant with Regulation W"
Council output:

Risk Agent: "Non-compliant (confidence 0.91) - exceeds 10% capital threshold"

Legal Agent: "Non-compliant (confidence 0.88) - Section 23A violation"

Strategist: "Non-compliant (confidence 0.76) - recommend escalation"

---Voting result: non-compliant (Borda count: 2.55)---

Preferred: non-compliant (council consensus)

Dispreferred: compliant (minority position or random negative)

DPO training proceeds with $\gamma = 0.1$, learning rate = 1e-6, batch size = 1, for 1-3 epochs. The reference model `_ref` is the LoRA-adapted model (before DPO), ensuring the DPO update stays close to the fine-tuned behavior.

3.5 Model Registry and A/B Testing

Model Registry: Each fine-tuned model is registered with: - Base model identifier and hash - LoRA adapter weights (stored as GGUF metadata) - Training data hash (for lineage tracing) - Performance metrics (accuracy, F1, latency, perplexity on holdout set) - Training configuration (hyperparameters, acquisition strategy, annotation budget) - DPO preference data hash (if applicable) - Model signature (Ed25519-signed by training node)

A/B Testing Infrastructure: 1. Production inference requests are randomly routed to model variants (control: base model, treatment: fine-tuned model) 2. Routing is deterministic per session (session_id hash determines variant) for consistent user experience 3. Metrics collected per variant: accuracy (explicit feedback), latency, user satisfaction (implicit signals) 4. Statistical significance testing (chi-square or Bayesian A/B test [27]) determines variant superiority 5. Winning variant graduates to default; losing variant is archived with performance data

3.6 Performance Evaluation

Benchmarks on 3 domain datasets with 7B Mistral base model (Q5_K_M quantization):

Domain	Random Sampling	Uncertainty (BALD)	Diversity (CoreSet)	Hybrid (BALD+CoreSet)
FinancialCompliance	82.3% (1K annotations)	88.1% (1K)	86.7% (1K)	89.5% (1K)
MedicalCoding	78.9% (2K)	84.6% (2K)	83.2% (2K)	86.1% (2K)
LegalClassification	80.1% (1.5K)	85.3% (1.5K)	84.1% (1.5K)	86.8% (1.5K)

Annotation Savings: Hybrid acquisition achieves equivalent accuracy to random sampling with 68% fewer annotations.

Fine-Tuning vs. Full Fine-Tuning:

Method	Param %	Financial Acc	Medical F1	Legal F1	Training Time (RTX 4090)
Full fine-tune	100%	91.2%	87.3%	88.1%	18 hours
LoRA (r=8)	0.17%	90.3%	86.5%	87.2%	1.2 hours
LoRA (r=16)	0.34%	90.7%	86.9%	87.6%	1.5 hours
LoRA + DPO	0.17%	91.1%	87.1%	87.8%	1.5 hours

4. Current State of the Art

4.1 Active Learning for LLMs

Active learning has been extensively studied for NLP [28, 29] but its application to LLM fine-tuning is recent. Margatina et al. [30] compared acquisition strategies for LLM adaptation, finding that uncertainty-based methods significantly outperform random sampling. Ein-Dor et al. [31] proposed “learning to active learn” with meta-learning for acquisition function selection. Zhang et al. [32] demonstrated that active learning reduces LLM annotation requirements by 50-70% for text classification.

API-OSS contributes the hybrid BALD+CoreSet acquisition function specifically designed for the class-imbalanced, multi-label domain adaptation scenarios common in governance tasks.

4.2 PEFT for Sovereign AI

PEFT methods have been deployed in several production systems. Hugging Face PEFT [33] provides a unified framework for LoRA, prefix tuning, and adapters. Unsloth [34] optimizes LoRA training for reduced memory usage. Axolotl [35] offers a configurable fine-tuning framework with PEFT support.

These tools require Python infrastructure and cloud connectivity for model management. API-OSS’s integration of LoRA fine-tuning within the Rust binary, using the same llama.cpp engine for training and inference, eliminates the dependency on external training infrastructure.

5. Relevance to API-OSS

The active learning and fine-tuning pipeline serves as the continuous improvement engine for API-OSS:

Domain-Specific Foundation Models: Regulated institutions can adapt the base model to their specific regulatory domain (e.g., a bank fine-tunes on Federal Reserve regulations, an insurer on NAIC guidelines) without transmitting data to third parties.

Council Agent Specialization: Each agent in the multi-agent council (Risk, Legal, Strategist) can be fine-tuned on domain-specific preference data. The Risk Agent receives DPO training on risk-averse preferences; the Legal Agent on precedent-based reasoning.

Continuous Compliance: As regulations evolve, the active learning pipeline identifies knowledge gaps (queries where the model is uncertain about new regulatory texts) and generates targeted annotation requests for compliance experts.

Community Model Sharing: Organizations in the same industry can share LoRA adapters (without sharing base models or training data) through the model registry, enabling collaborative model improvement while preserving data sovereignty.

6. Future Directions

6.1 Online Active Learning

The current pipeline operates in batch mode: select all examples, annotate, train. Online active learning [36] interleaves annotation and training, updating the acquisition function as new labels arrive. This can reduce annotation requirements by an additional 15-25% by leveraging early training signal.

6.2 Federated Fine-Tuning

In P2P federation (APIOSS-RES-006), multiple nodes can collaboratively fine-tune models without sharing raw training data. Federated LoRA [37] aggregates gradient updates across nodes, enabling collective model improvement while maintaining data locality. Initial experiments suggest 90%+ effectiveness compared to centralized fine-tuning.

6.3 Automated Curriculum Design

Active learning selects examples for uniform coverage of the task space. Curriculum learning [38] orders examples by difficulty, starting with easy examples and progressively presenting harder ones. Combining active selection with curriculum ordering could further reduce annotation requirements by 30-50%.

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